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LEVERAGING EFFICIENTNET-B4 IN GOAT DISEASE PREDICTION AND RECOMMENDATION SYSTEMS FOR MORTALITY REDUCTION AND HEALTH OPTIMIZATION

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ABSTRACT

Goat farming is a supplementary business to agriculture for Indian farmers, contributing significantly to India's agricultural economy and growth. When a goat gets infected with some disease, the expense of treating a sick goat frequently exceeds the money that could be made from selling the animal. Additionally, there is a risk that the sickness could infect other goats, leading farmers to isolate the sick goat from the rest of the flock. Due to the low survival rate and reduced weight of the goat after recovery, farmers usually concentrate less on treating the infected goat, as it is unlikely to be profitable even if it survives. In this research, we build a deep learning-based framework to address the problem of early disease identification in goats. A dataset of 1960 images, representing six major goat diseases, was prepared by visiting different goat farms. The preliminary preprocessing techniques, including image resizing, normalization, and noise reduction, were applied to the collected dataset of goat disease images in order to enhance the quality and consistency to boost model training and performance. Several architectures, including CNN, AlexNet, VGG-19, ResNet-50, and EfficientNet-B4, were trained on gathered data and evaluated using evaluation measures. Among all the architectures evaluated, EfficientNet-B4 achieved an excellent accuracy of 93%, demonstrating its robustness and efficiency in diagnosing goat sickness. In comparison, CNN achieved 72%, AlexNet delivered 79%, VGG-19 delivered 77%, and ResNet-50 delivered 89% accuracy. The proposed framework demonstrates strong potential as a feasible option for real-time goat health monitoring, offering farmers a useful tool for assisting with early detection and prevention. This advancement can accelerate efforts toward achieving sustainable and profitable livestock production in rural India.
Keywords: *Goat Farming, Disease Prediction, EfficientNet-B4, Livestock, Health.*

1. INTRODUCTION

India has a livestock population of approximately 537 million, out of which 150 million are goats and 75 million are sheep. Goat farming serves as a secondary source of income for Indian farmers, helping them manage immediate and unexpected expenses, particularly in rural areas. Goat farming has become known as a viable alternative livelihood option for small-scale farmers, particularly in rural and semi-rural areas, because it is simple for farmers to adopt and manage 2–3 goats alongside their core agricultural activity. With rising demand for goat meat and market prices, goat farming is a feasible and profitable option for farmers with limited resources and land [1].

However, the number of new goat farming ventures initiated each year is lower than the number that shut down due to heavy losses. Key reasons for goat mortality, and consequently, business failure, include lack of vaccination, sudden weather changes, and inadequate veterinary care [2]. Veterinary consultation and medication costs often reduce profit margins, with treatment expenses sometimes exceeding the selling price of a goat. Table 1 provides a detailed breakdown of expenses for a single goat's expenses and returns, including feed, treatment, weight, and profit.

Table 1: Detailed Expense and Return Breakdown for a Single Goat

Category	Details	Estimated Cost (₹)
Initial Cost (Kid)	Cost of newborn goat (if not homebred)	1,500
Feeding (8 to 10 months)	Fodder, supplements, minerals	2,000
Shelter and Maintenance	Space, water, cleaning	500
Vaccination and Deworming	Regular preventive healthcare	300
Treatment (if sick)	Average medicine/vet charges	800
Labor/Time Cost	Farmer effort/time (approximate)	400
Miscellaneous	Transportation, insurance, tagging, etc.	500
Total Cost		**6000**
Goat Selling Price (10 Months)	Average Weight: 30kg Average Selling Price: 400 per kg	12000
Profit		**6000**

Although a profitable secondary option, goat farming suffers several critical challenges that restrict its sustainability and growth among small-scale farmers:

- Spreading of Infection Quickly: Goats are extremely susceptible to contagious infections, which can spread quickly within a herd due to close living conditions and a lack of prompt isolation, resulting in high fatality rates [3].
- High Treatment Costs: Veterinary treatments and drugs are frequently expensive, making it difficult for small-scale farmers to afford treatment. In many situations, the treatment costs exceed the market value of the diseased goat, resulting in a financial loss [4].
- Unavailability of Veterinary Doctors: In many remote regions, veterinary doctors are not easily accessible when needed. Even when they are available, delays in reaching the location are common due to their hectic schedules and numerous appointments [5].
- Lack of Awareness and Timely Diagnosis: Many farmers are unable to notice early signs of sickness because of a lack of knowledge, resulting in late diagnosis and decreased likelihood of recovery.
- Post-Recovery Loss in Productivity: Even if a goat recovers after rigorous treatment and care, it often suffers from significant weight loss and reduced vitality [6].

The expense table provides evidence that if a goat becomes infected, the whole treatment cost rises dramatically. In addition to the costly burden of veterinary care, the goat's health deteriorates, especially in terms of weight loss and decreased vitality [7]. Because the market price of a goat primarily depends on its live weight, this drop has a direct impact on the selling price, resulting in reduced profit margins or possibly a net loss for the farmer [8]. Therefore, early detection and prevention of illness are essential for preserving profitability in goat farming. A more effective solution is the early detection of diseases and timely intervention before the condition worsens [9, 10].

In this study, we collected goat disease images from multiple farms, considering variations in goat color and appearance. The collected dataset was used to train an EfficientNet model to identify disease categories and provide immediate treatment suggestions. The proposed model was evaluated using standard performance metrics and compared with other deep learning algorithms trained on the same dataset. Results show that the proposed model outperforms existing alternatives, offering faster and more accurate predictions along with relevant treatment advice. This model can assist farmers in early disease detection, enabling prompt action and ultimately improving productivity and profitability. Farmers receive recommendations from the system according to the disease's identification, such as causes, severity, potential for transmission, available primary treatment choices, and essential measures. It enables farmers to take timely action to prevent the spread and support the goat's immediate or early recovery. Precision livestock farming, a technology-driven approach that improves animal health monitoring, may be assisted practically by this intelligent system, which can also greatly contribute to improved disease management and sustainable agricultural methods in rural India.

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2. LITERATURE SURVEY

The application of deep learning algorithms to livestock disease identification has produced promising results for enhancing animal health management. D. Machuve et al. investigated the use of deep learning approaches for early diagnosis of chicken diseases using fecal image categorization. The study looks at three common poultry diseases: coccidiosis, salmonella, and Newcastle disease, as well as healthy samples. The study examined various Convolutional Neural Network (CNN) architectures, including a baseline CNN, VGG16, InceptionV3, MobileNetV2, and Xception. Models were trained on 8,067 photos tagged both in the lab and on farms. The baseline CNN has an accuracy of 83.06%, while VGG16 has 95.01%, InceptionV3 has 95.45%, and MobileNetV2 has the highest accuracy at 98.02%. This study highlights the effectiveness of deep learning models, particularly MobileNetV2, in adequately discovering chicken diseases using fecal images, thus offering an efficient method for early identification of diseases in poultry, particularly in situations with limited resources [11].

Using wearable sensors and an improved backpropagation (BP) neural network model, W. Fan et al. demonstrated a smart livestock health monitoring system. The technology was created to collect and evaluate physiological data, including body temperature, heart rate, and activity levels, in real time in order to forecast the small-tailed cold sheep's health. The wearable sensor gadget is used by the system to gather data from 36 sheep in a variety of health categories. SLBAS-BP is an enhanced version of the BP neural network that was created to increase prediction accuracy and convergence speed. It includes features like momentum factors and customizable learning rates. The model was trained to categorize health status as healthy, sub-healthy, feverish, or diseased through continuous sensor measurements. The model gained prediction accuracies of 98% for healthy, 94% for sub-healthy, 90% for fever, and 98% for illness conditions, indicating great dependability in identifying different health stages. The major limitation identified is that wearable sensors provide real-time monitoring, but they may not be practical or cost-effective for small-scale farmers due to initial expenditures, maintenance, and the need for constant power and connectivity. Furthermore, sensor malfunction or poor attachment to the animal can result in false data, reducing the reliability of the health prediction model [12].

The assessment of Body Condition Score is critical for monitoring the health and productivity of precision livestock farming, and standard BCS evaluation methods based on manual observation are labor-intensive. To resolve these problems, A. Temenos et al. invented lightweight Goat-CNN, which automates BCS estimation in goats regardless of their position. The dataset of 5,000 photos presenting the dorsal view of goat backsides used to train Goat-CNN focuses on low computational complexity, making it appropriate for deployment on edge devices connected with IoT. The proposed Goat-CNN gained 97.9% accuracy against comparable architectures such as VGG, ResNet, DenseNet, and GoogleNet. The proposed Goat-CNN performance is affected by parameters such as lighting conditions, occlusions, and camera angles, which might influence image quality, and the model's effectiveness in different breeds requires additional validation [13].

As lumpy skin disease (LSD) is a highly contagious viral disease that affects cattle and leads to significant financial losses due to decreased milk production, reproduction issues, and even fatalities, early and precise detection is essential for disease control. The study by D. K. Saha offers an in-depth analysis of several different CNN architectures for the automated detection of LSD in dairy cows. The study constructed a dataset of 840 pictures from two distinct agro farms to ensure diversity, with 513 images of healthy cows and 327 pictures of cows affected by LSD. Image scaling and segmentation were used during the preprocessing processes to separate the infected areas. Using Gray Level Co-occurrence Matrix (GLCM) approaches, ten different features were extracted from the photos. Among the CNN models evaluated, MobileNetV2 outperformed and delivered the highest accuracy of 96% and AUC of 98%, as compared to DenseNet201 (94% accuracy, 97% AUC) and traditional ML models like SVM (78% accuracy), highlighting MobileNetV2's suitability for real-time, resource-constrained environments. The study's limitations involve an imbalanced dataset and a particular emphasis on LSD, which may limit the model's applicability to other cattle diseases [14].

To ensure animal health and reduce disease outbreaks in goats, sheep, and cattle, D. Girmaw presents a deep learning-based system constructed to automatically detect and classify skin disorders. The study obtained 1,405 photos of livestock skin disorders from Haramaya University's College of Veterinary Medicine in Ethiopia, and veterinary professionals assisted in identifying the disease categories as sheep pox, LSD, contagious ecthyma, and dermatophilosis. The study assessed several pre-trained deep learning models fine-tuned using transfer learning to adapt to the livestock disease dataset, revealing that EfficientNetB7 performed the best, with a classification accuracy of 99%. The study's limitations include the fact that data was obtained from just one organization, the model's performance in different contexts or geographic regions may differ, and only skin illnesses were evaluated, limiting the scope of the diagnostic system [15].

Deep learning is especially well-suited for livestock management due to its potential to extract complicated patterns from unstructured data. With the growing integration of smart agricultural technology, behavior detection based on sensor data and camera footage has emerged as an important tool for livestock management. A. Rohan et al. conducted an assessment of 92 peer-reviewed articles published between 2012 and 2022 on livestock, specifically cattle, pigs, and poultry, to categorize the studies based on the type of sensor employed, the deep learning architecture used, and the targeted behaviors. The findings revealed that CNNs were mostly used for video-based behavior recognition, particularly in poultry and cattle. LSTM and hybrid CNN-LSTM models performed effectively while processing time-series data from wearable sensors to detect pig and cattle activity. Models achieved better than 90% accuracy in identifying simple behaviors, but performance dropped when separating complex or overlapping tasks [16].

S. Swain et al. used machine learning models to forecast cow diseases based on various health metrics and environmental factors, such as body temperature, water intake, heart rate, humidity, etc., collected using IoT-enabled sensors. The study compares the performance of Naïve Bayes Multinomial, Lazy-IBk, Partial Tree, Random Forest, and Support Vector Machine models in predicting cattle health based on physiological and environmental factors. The study uses a dataset of 2,000 samples collected from sensors for 14 health categories. The study found that the Random Forest model performed the best, with an accuracy of 96%, followed by PART and SVM. The study's limitation is that it merely examines specific symptoms of disease and does not generalize across breeds or geographical regions. It does not include real-time streaming or edge computing, which are critical for on-farm deployment [17].

H. Byeon et al. demonstrate the rising use of artificial intelligence (AI) in animal healthcare, particularly in preliminary illness verification, to reduce diagnostic time, increase precision, and help veterinarian decision-making. The development of deep neural networks (DNNs) was an important advancement in disease prediction. DNNs can learn hierarchical features directly from data, making them extremely useful for complicated tasks like image recognition, audio processing, and disease prediction. However, DNNs have some limitations, especially training instability and slower convergence due to their reliance on gradient descent optimization. To solve these challenges, broad learning (BL) is an alternative approach that ignores gradient descent and enables quick model rebuilding using incremental learning, considerably speeding up training. The BL model is not capable of successfully extracting complicated features from data, especially in fields such as healthcare, where the relationships between features are frequently complex. The author proposed a hybrid model, ABL (Autoencoder-Based Broad Learning), that combines the advantages of broad learning and denoising autoencoders to gain accuracy of up to 98.50% [18].

3. METHODOLOGY

The present study emphasizes implementing deep learning models to classify goat conditions. The dataset consists of pictures presenting six distinct goat diseases, as well as an additional category for healthy goats, which are rigorously preprocessed to improve model performance. Preprocessing steps cover all basic strategies, including scaling all photos to a uniform resolution, standardizing pixel values, and using data augmentation techniques like rotation, flipping, and zooming to increase dataset diversity and reduce overfitting. Following preprocessing, several deep learning architectures are examined to assess how effective they are in disease classification, including CNN, AlexNet, VGG-19, ResNet-50, and EfficientNet, trained on the same dataset split to provide a fair comparison. The models are evaluated using evaluation metrics, and EfficientNet has been demonstrated to be the most effective model, delivering high accuracy while taking up little computing time in terms of epoch. An image of a goat captured in real time is fed into the trained EfficientNet model for identifying the presence and type of sickness. In addition to the forecast, the system gives important information such as possible causes, disease spread rate,

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recommended treatments, and potential consequences if not addressed, represented in Figure 1. This allows goat producers and veterinarians to make more rapid and informed decisions. The primary goal of the proposed system is to accurately diagnose goat diseases and provide immediate feedback, such as the cause, potential effects, and suggested therapies. This proactive strategy helps prevent the spread of infection to other goats and reduces health risks in circumstances where quick veterinary assistance is unavailable. Timely treatment prevents the affected goat from progressing to a serious condition and increases the likelihood of a faster recovery.

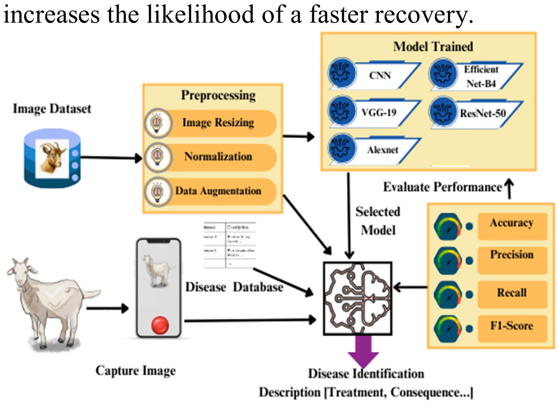

Figure 1: Architecture of the Proposed Goat Disease Prediction and Recommendation System

3.1 Dataset Description and Preprocessing

We have collected 1960 images for six goat diseases and one healthy class from multiple farms, considering variations in goat color and appearance. We have collected a total of 1920 pictures from multiple farms, covering five different goat disease categories and one healthy class. The dataset had been carefully selected to account for variation in goat color, breed, and appearance, ensuring model diversity and generalizability. To ensure uniformity and increase model performance, all gathered pictures went through a comprehensive preprocessing process. Images were initially resized to 224×224 pixels to comply with the CNN architecture's input dimension requirements [19].

To scale pixel values to the [0, 1] range, normalization was employed, leading to faster convergence during training. Furthermore, data augmentation techniques such as random rotation, horizontal flipping, zooming, and brightness correction were employed to improve dataset heterogeneity while lowering the possibility of overfitting [20]. The dataset was then divided into three subsets: training (70%), validation (20%), and testing (10%), with class balance preserved across all of them. The dataset includes pictures of six goat diseases: caseous lymphadenitis (CLA), foot-and-mouth disease (FMD), diarrhea, anemia, dermatophilosis, and mastitis, as well as an additional category for healthy goats. The detailed description for each category has been given below.

- CLA: Corynebacterium pseudotuberculosis causes a chronic bacterial disease known as caseous lymphadenitis. It typically affects goats and sheep and can be identified by the formation of abscesses in lymph nodes and internal organs, especially the lungs and liver. The symptoms include swelling of external lymph nodes, especially around the neck and jaw; formation of thick-walled abscesses that may rupture; weight loss; and decreased milk/meat production. In internal cases, symptoms include prolonged coughing and respiratory trouble.
- FMD: FMD is a highly transmittable viral infection that affects cloven-hoofed animals such as goats, sheep, cattle, and pigs, caused by the FMD virus (FMDV), which belongs to the Picornaviridae family. FMD in goats causes fever, excessive salivation, lesions in the mouth and on the feet, inability to move, decreased hunger, and a considerable drop in the amount of milk produced [21].
- Diarrhea: Diarrhea in goats can be triggered by a number of reasons, including infectious bacteria such as E. coli and Salmonella, parasite infections such as coccidiosis or worms, and nutritional difficulties, including sudden changes in feed or low-quality food. Diarrheal symptoms are frequent loose or watery stools, dehydration, weight loss, and poor appetite.
- Anemia: Anemia in goats is a condition in which the total amount of red blood cells or hemoglobin is less than normal, reducing the capacity of the blood to transport oxygen. Common symptoms include pale eyelids, Weakness and lethargy Poor appetite or abrupt weight loss, A swollen jaw, Rough or dull hair [22].
- Dermatophilosis: It is a bacterial skin infection caused by Dermatophilus congolensis in goats, frequent in rainy or

humid circumstances where the skin stays moist for lengthy periods of time, allowing germs to penetrate. The symptoms include the formation of crusty, scabby sores on the back, neck, face, and legs, as well as pain and discomfort.

- Mastitis: Mastitis is an ordinary, potentially deadly bacterial infection of the goat's mammary glands that causes swelling and reduced production of milk. Signs comprise swelling and pain in the udder, clumpy milk, and a considerable decrease in milk production [23].

Figure 2 demonstrates the sample images from the dataset representing six goat diseases, such as CLA, FMD, diarrhea, anemia, dermatophilosis, and mastitis, along with images of healthy goats.

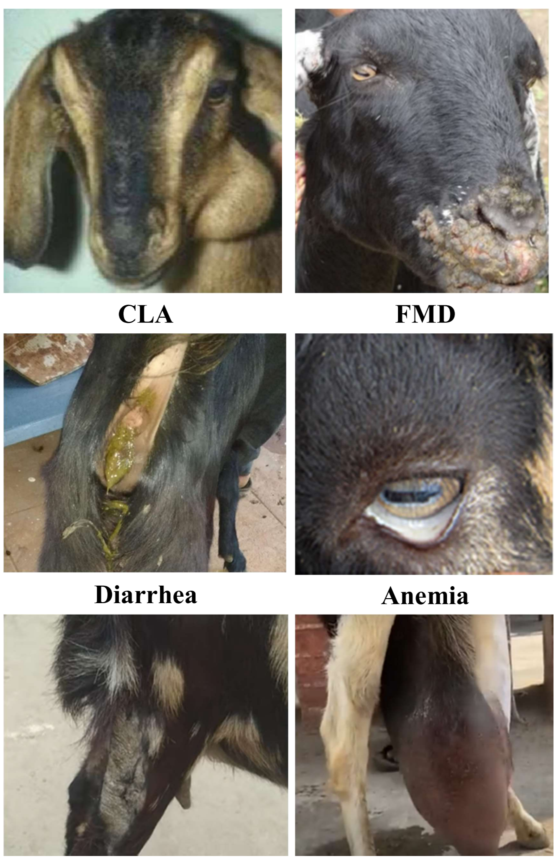

Figure 2: Representative Images of Different Goat Diseases in the Dataset

3.2 EfficientNet-B4 Architecture

The Google researchers developed the EfficientNet-B4, which belongs to the EfficientNet family, to increase the efficiency of CNN using a variety of scaling strategies. The EfficientNet models aim to deliver greater performance with fewer parameters by optimizing the network's depth, breadth, and resolution. EfficientNet utilizes three scaling methods: depth (number of layers), breadth (number of filters per layer), and resolution (size of input image). EfficientNet-B4, with its compound scaling technique and efficient architecture, is an effective framework for fine-grained image classification tasks such as goat disease forecasting. EfficientNet-B4 is composed of Mobile Inverted Bottleneck Convolution (MBConv) blocks associated with Squeeze-and-Excitation (SE) optimization and compound scaling [24].

Stem Layer: The stem layer is the primary layer in the EfficientNet-B4 architecture, similar to the "entry gate" of the neural network, responsible for interpreting the input image and reducing its spatial dimensions from 380×380 to 190×190 while boosting feature depth.

MBConv Block: MBConv blocks boost efficiency and accuracy by combining the principles of depthwise separable convolutions, expansion layers, and SE modules.

$$\mathrm{MBConv}(\mathrm{x}) = \mathrm{x} + \mathrm{P}\left(\mathrm{SE}\left(D_k\left(\mathrm{E}(\mathrm{x})\right)\right)\right) \qquad (1)$$

where E is the expansion factor, such as 6; Dk is the depthwise convolution with kernel size k; SE is the squeeze-and-excitation block; and P is the projection layer (1×1 convolution).

Squeeze-and-Excitation Block: The SE block is a lightweight operational component that enhances the functional capacity of a convolutional neural network by simulating interdependencies across feature channels. Conventional convolutional layers treat each feature channel separately, without explicitly modeling their relative significance to the task. The SE block overcomes this restriction by squeezing global spatial information into a channel description and exciting each channel with a learned relevance weight [25]. The spatial dimensions are compressed using global average pooling to generate a channel descriptor using the following equation.

$$Z_c = \frac{1}{H\,x\,W}\sum_{i=1}^{H}\sum_{j=1}^{W} X_{i,j,c} \quad for\ c=1,2,\ldots C \qquad (2)$$

For a given input Given an input tensor $X \in R^{H\times W\times C}$, the H and W are spatial dimensions, C is the number of channels, and the results in a vector $z \in R^{C}$. To learn channel-wise dependencies, the excitation operation passes the descriptor vector through two fully connected (FC) layers with non-linear activations represented in Equation 3.

$$s = \sigma\big(W2 \cdot \delta(W1 \cdot z)\big) \qquad (3)$$

Where $W1 \in R^{c/r\times C}$, $W2 \in R^{C\times C/r}$, δ is ReLU, σ is the sigmoid activation function, and r is the reduction ratio, typically set to 4, 8, or 16 [26].

Batch Normalization*:* Batch normalization (BN), a significant technique in deep neural networks, removes the problem of internal covariate shift by normalizing the inputs to each layer, resulting in a mean of zero and a standard deviation of one. The batch normalization layer determines the mean and variance of activations for each feature in a mini-batch, as demonstrated below.

$$Mean\ (\mu_B) = \frac{1}{m}\sum_{i=1}^{m} x_i \qquad (4)$$

$$Variance(\sigma_B^2) = \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_B)^2 \qquad (5)$$

Where m represents the total quantity of samples in the mini-batch, and for the i^{th} input, x is the activation value. To normalize each activation, x, the computed mean and variance are then used [27].

$$\widehat{X} = \frac{x_i - \mu\beta}{\sqrt{\sigma_\beta^2 + \epsilon}} \qquad (6)$$

Where μβ represents the mean and σ_β^2 represents the variance of the batch. A minor constant ϵ is added to prevent division by zero.

Compound Scaling: Instead of raising depth, breadth, or input resolution arbitrarily, EfficientNet scales all three dimensions simultaneously using a compound coefficient ϕ.

$$\text{Depth (d)} = \alpha^{\phi}, Width\ (w) = \beta^{\phi}, \text{Resolution (r)} = \gamma^{\phi} \qquad (7)$$

The scaling factors for EfficientNet-B4, where ϕ=4, are α=1.8, β=1.1, and γ=1.15, which optimizes computational performance while increasing model capacity. This results in a network that is roughly 10.5× deeper, 1.46× broader, and processes input images at 1.75× greater resolution than the baseline, EfficientNet-B0.

Researchers at Google invented the Swish activation function, which is smooth and non-monotonic. It has been demonstrated to outperform classic activation functions such as ReLU in deep networks, and it is utilized as the default activation function in the EfficientNet family, including EfficientNet B4 represented in Equation 8.

$$Swish(x) = x \cdot \sigma(x) = \frac{x}{1+e^{-x}} \qquad (8)$$

Where x represents the input to the activation function and σ(x) represents the sigmoid function [28]. Table 2 summarizes the architectural details for EfficientNet-B4, covering layer names, input and output sizes, filter dimensions, kernel size, and stride values.

Table 2: Architectural Specifications of EfficientNet-B4 Including Layer Configuration, Input/Output Sizes, and Kernel Details

Stage	Layer Name / Block	Input Size	Output Size	Filter / Kernel
0	Stem Conv2D	380×380×3	190×190×48	**Filter:** 3×3, **Stride:**2, **Layers:**1
1	MBConv1 (Fused)	190×190×48	190×190×24	**Filter:** 3×3, **Stride:**1, **Layers:**1
2	MBConv6	190×190×24	95×95×32	**Filter:** 3×3, **Stride:**2, **Layers:**2
3	MBConv6	95×95×32	48×48×56	**Filter:** 5×5, **Stride:**2, **Layers:**2
4	MBConv6	48×48×56	24×24×112	**Filter:** 3×3, **Stride:**2, **Layers:**3
5	MBConv6	24×24×112	24×24×160	**Filter:** 5×5, **Stride:1**, **Layers:**3
6	MBConv6	24×24×160	12×12×272	**Filter:** 5×5, **Stride:2**, **Layers:**4
7	MBConv6	12×12×272	12×12×448	**Filter:** 3×3, **Stride:1**, **Layers:**1
8	Conv2D + BN + Swish	12×12×448	12×12×1792	**Filter:** 1×1, **Stride:1**, **Layers:**1
9	Global Average Pooling	12×12×1792	1×1×1792	**Layers:**1
10	Dropout (0.4)	1×1×1792	1×1×1792	**Layers:**1
11	Dense (Classifier)	1×1×1792	1×1×C	**Layers**:1

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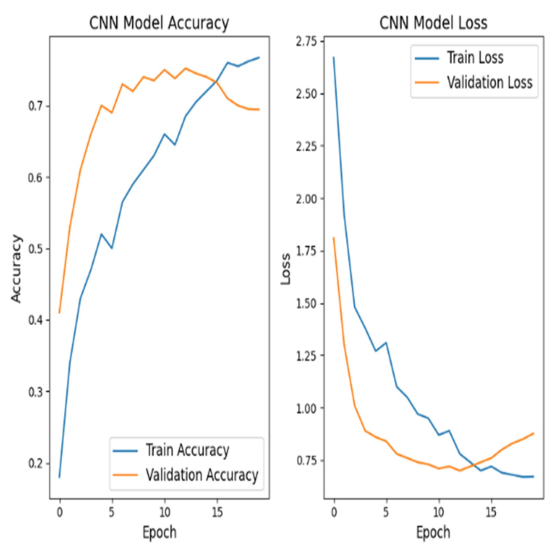
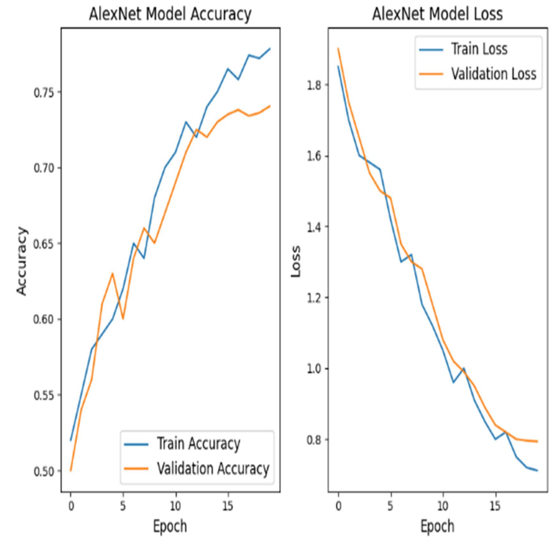
4. RESULT AND DISCUSSION

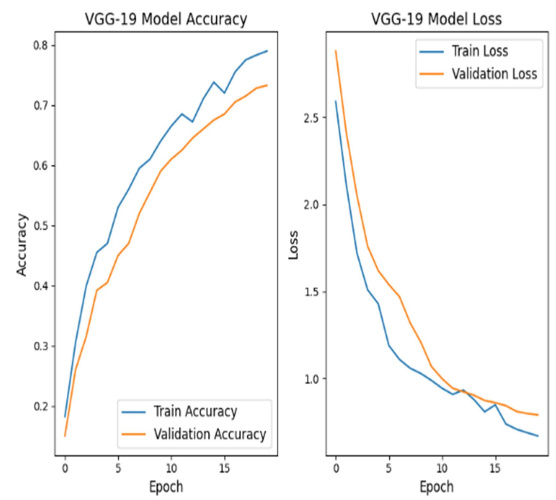
The proposed goat sickness categorization framework was implemented and tested in a cloud-based environment making use of Google Colab, which provides free GPU resources for faster model training. The experiments were carried out with Python 3.10 and important libraries such as TensorFlow, Keras, NumPy, Matplotlib, and scikit-learn. The models were trained using the TensorFlow 2.x framework with the Keras API on a Colab-provided NVIDIA Tesla T4 GPU with 12 GB of RAM. The input photos were scaled to 224 × 224 pixels using a batch size of 32, and the total number of training epochs was set to 25. The Adam optimizer has been used in combination with the categorical cross-entropy loss function. The 1960 images dataset for six goat diseases and one healthy class was partitioned into three sets: training, validation, and testing, in the ratio 70:20:10. To ensure a fair comparison, all deep learning models (CNN, AlexNet, VGG-19, ResNet-50, and EfficientNet) were trained under the same environments. Figure 3 demonstrates the training and validation accuracy, along with the loss curves for each deep learning model implemented in this work. These graphs assist in visualizing the models' performance and generalization capabilities across epochs.



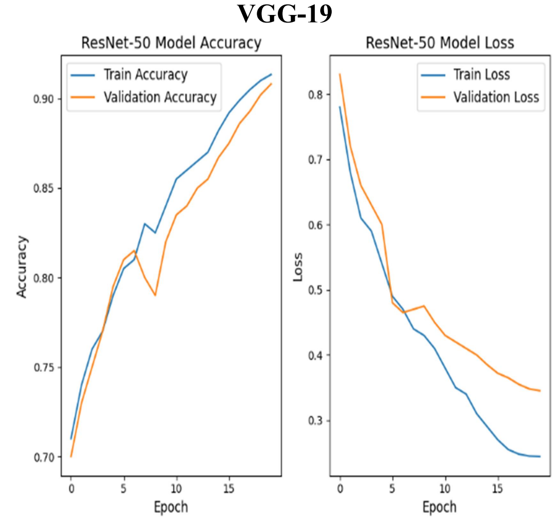
CNN



AlexNet



VGG-19



ResNet-50

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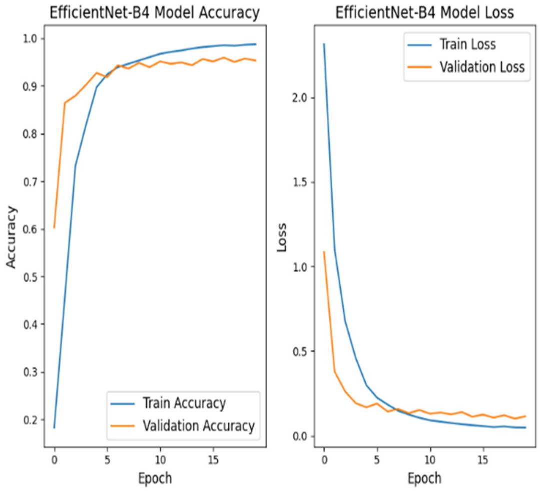

EfficientNet-B4

Figure 3: Training, Validation Accuracy, and Loss Curves for Different Models

The experimental results demonstrate that EfficientNet-B4 delivered more substantial classification performance and achieved convergence in just 7 epochs, which made it the most effective model in terms of training speed and accuracy. The CNN model, on the other hand, demonstrated substantial variations in training and validation accuracy, implying probable overfitting and lower generalization capacity. Additionally, AlexNet, VGG-19, and ResNet-50 demonstrated rather consistent training behavior but needed more epochs to reach convergence.

To evaluate the trained models' generalization abilities and practical use, an additional test dataset of 196 photos was created, comprised of samples from all seven classes, averaging 28 photos per class, and none of these pictures were utilized for training or validation, assuring an unbiased assessment. The confusion matrix for each model was created to visually examine classification performance across all classes to determine which classes are frequently confused with others, providing a more in-depth understanding of model behavior shown in Table 3. Key performance indicators like accuracy, precision, recall, and F1-score [29, 30] have been estimated to assess the models' effectiveness presented in Table 4.

Table 3: Confusion Matrices for Test Image Classification Across Different Models

Model	Category	CLA	FMD	Diarrhea	Anemia	Dermatophilosis	Mastitis	Healthy
CNN	CLA	19	3	1	3	1	0	1
	FMD	2	19	1	2	1	1	2
	Diarrhea	0	0	23	1	2	2	0
	Anemia	2	2	0	20	2	1	1
	Dermatophilosis	1	0	2	0	20	3	2
	Mastitis	1	0	4	0	2	18	2
	Healthy	1	0	2	0	1	3	22
AlexNet	CLA	23	2	1	1	0	0	1
	FMD	1	22	2	1	1	0	1
	Diarrhea	0	0	23	0	3	2	0
	Anemia	2	0	1	21	1	1	2
	Dermatophilosis	0	0	1	0	23	2	2
	Mastitis	0	1	2	0	2	20	2
	Healthy	1	0	0	0	3	3	22
VGG-19	CLA	12	1	2	1	1	0	1
	FMD	1	22	2	1	1	0	1
	Diarrhea	0	0	23	0	3	2	0
	Anemia	2	0	1	21	1	1	2
	Dermatophilosis	0	0	2	0	23	1	2
	Mastitis	0	1	4	0	2	18	2
	Healthy	2	0	1	0	1	3	22
ResNet-50	CLA	23	2	1	1	0	0	1
	FMD	0	24	3	1	0	0	0
	Diarrhea	0	0	27	0	1	0	0
	Anemia	1	1	0	25	0	0	1
	Dermatophilosis	0	0	0	0	25	2	1
	Mastitis	0	0	0	0	2	24	1
	Healthy	0	0	0	0	1	2	26
Efficient Net-B4	CLA	26	2	1	0	0	0	0
	FMD	2	25	0	0	0	0	0
	Diarrhea	0	0	27	1	0	0	0
	Anemia	0	0	0	27	1	0	0
	Dermatophilosis	0	0	0	0	26	1	1
	Mastitis	0	0	0	0	0	25	2
	Healthy	0	0	0	0	0	2	27

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Table 4: Evaluation Metrics for Model Performance on Test Images Performance Evaluation Metrics for Test Image Classification

Model	Accuracy	Precision	Recall	F1-Score
CNN [31, 32]	0.72	0.72	0.72	0.72
AlexNet [33, 34]	0.79	0.79	0.79	0.79
VGG-19 [35, 36]	0.77	0.78	0.77	0.77
ResNet-50 [37,38]	0.89	0.89	0.89	0.89
EfficientNet-B4	0.93	0.93	0.93	0.93

The experimental outcomes demonstrate that EfficientNet-B4 beats the other models examined in terms of overall accuracy and other key performance parameters. Among all the architectures examined, EfficientNet-B4 achieved the greatest accuracy of 93%, proving its robustness and effectiveness in goat sickness diagnosis. In comparison, CNN achieved 72%, AlexNet reached 79%, VGG-19 obtained 77%, and ResNet-50 delivered 89% accuracy. The confusion matrix highlighted EfficientNet-B4's outstanding classification potential, as it diagnosed disease categories with high precision, demonstrating its promise for dependable real-world implementation in veterinary diagnostics. Even with the relatively small dataset of 1960 images across six disease classes, EfficientNet-B4 demonstrated the highest accuracy among all tested models. This performance is primarily due to its effective compound scaling technique, which more efficiently balances the model's depth, width, and input resolution than conventional architectures. When data is limited, these balanced scaling is particularly significant since it allows the network to learn richer and more specific features without overfitting.

5. CONCLUSION AND FUTURE SCOPE

Goat farming serves as a supplementary source of income for many farmers. However, when a goat becomes infected with a disease, there is a high risk of transmission to other goats, leading to increased treatment costs, potential fatalities, and reduced profitability. In the absence of on-time veterinary attention, the infection can quickly deteriorate, spreading across the herd and perhaps leading to an unexpected death. In this study, deep learning algorithms have been implemented to identify goat sickness in image data. The collection included pictures from six disease categories and one healthy category. Several models, including CNN, AlexNet, VGG-19, ResNet-50, and EfficientNet-B4, were trained and evaluated using assessment metrics. EfficientNet-B4 outperformed the others, achieving the highest accuracy and consistently delivering results across multiple metrics. The model was effective at recognizing disease symptoms and has a high potential for use in real-world circumstances, particularly in distant places without immediate veterinary help. This approach provides an effective strategy for early diagnosis and appropriate intervention, ultimately assisting farmers in reducing losses and maintaining the health of their livestock. In the future, the dataset can be expanded to include more distinct pictures and diseases to increase the model's resilience. Incorporating additional features such as data on behavior, temperature, and geographic location could contribute to better forecast accuracy. Collaborations with veterinary institutes could assist validate the system with expert feedback and enable its usage in large-scale deployment. Additionally, the model can be expanded to include other livestock species and a larger spectrum of diseases.

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